Global Journal of Management and Business Research
Finance
Volume 13 Issue 3 Version 1.0 Year 2013
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 2249-4588 & Print ISSN: 0975-5853

Selection of Best ARIMA Model for Forecasting Average Daily Share Price Index of Pharmaceutical Companies in Bangladesh: A Case Study on Square Pharmaceutical Ltd.

By Dr. Jiban Chandra Paul, Md. Shahidul Hoque & Mohammad Morshedur Rahman
University of Chittagong, Bangladesh

Abstract - This work is an attempt to examine empirically the best ARIMA model for forecasting. Average daily share price indices of the data series of Square Pharmaceuticals Limited (SPL) have been used for this purpose. At first the stationarity condition of the data series are observed by ACF and PACF plots, then checked using the Statistics such as Ljung-Box-Pierce Q-statistic and Dickey-Fuller test statistic. It has been found that the average daily share price indices of the data series of Square Pharmaceuticals Limited (SPL) are non-stationary. The average daily share price indices of SPL data series are non-stationary even after log-transformation. But after taking first difference of logarithmic values of SPL data series, the same types of plots and the same types of statistics show that the data is stationary. The best ARIMA model have been selected by using the criteria such as AIC, AIC_c, SIC, AME, RMSE and MAPE etc. To select the best ARIMA model the data split into two periods, viz. estimation period and validation period. The model for which the values of criteria are smallest is considered as the best model. Hence, ARIMA (2, 1, and 2) is found as the best model for forecasting the SPL data series.

GJMBR-C Classification : *JEL Code: F37*

Strictly as per the compliance and regulations of:

Selection of Best ARIMA Model for Forecasting Average Daily Share Price Index of Pharmaceutical Companies in Bangladesh: A Case Study on Square Pharmaceutical Ltd.

Dr. Jiban Chandra Paul [α], Md. Shahidul Hoque [σ] & Mohammad Morshedur Rahman [ρ]

Abstract - This work is an attempt to examine empirically the best ARIMA model for forecasting. Average daily share price indices of the data series of Square Pharmaceuticals Limited (SPL) have been used for this purpose. At first the stationarity condition of the data series are observed by ACF and PACF plots, then checked using the Statistics such as Ljung-Box-Pierce Q-statistic and Dickey-Fuller test statistic. It has been found that the average daily share price indices of the data series of Square Pharmaceuticals Limited (SPL) are non-stationary. The average daily share price indices of SPL data series are non-stationary even after log-transformation. But after taking first difference of logarithmic values of SPL data series, the same types of plots and the same types of statistics show that the data is stationary. The best ARIMA model have been selected by using the criteria such as AIC, AIC_c, SIC, AME, RMSE and MAPE etc. To select the best ARIMA model the data split into two periods, viz. estimation period and validation period. The model for which the values of criteria are smallest is considered as the best model. Hence, ARIMA (2, 1, 2) is found as the best model for forecasting the SPL data series. Then, forecasts of the data have been made using selected type of ARIMA model. Finally, the values of ADSPI of SPL up to February 2012 are predicted and reported in the study.

I. Introduction

Stock exchange plays a vital role in the national economy of Bangladesh. Stock market is an essential part of the capital market. The economy of a country largely depends on capital market. In the capital market the investors invest the money to get the profit. The investors buy the security bond of different company on the priority basis. They choose the security bond of different company on the basis of the different factors. Some of the significant factors are Company's information analysis & prediction, dividend declaration, etc. A large amount of investors has no knowledge about the market analysis and proper prediction of the future prices of different types of shares available in the market. So, most of the time they spend the money to buy security bond of different companies on the basis of wrong and thumb idea, without any idea about data analysis and prediction.

For this reason there are extreme ups and downs in the daily share price indices, sometimes rise very quickly and fall sharply. In this situation, the market condition becomes unpredictable. Hence, a large amount of investors loss their capital in this unstable capital market. As a result the general investors do not find interest to invest the money in the capital market. Then there arises a crisis in the capital market which creates problem and hampers the national economic growth.

Therefore, if it is possible to provide a better model for the share market which can enable the investors to predict the prices in advance, it would help the investors as well as keep stability of the national economy. This study is an effort towards that direction.

Author α : Professor, Department of Statistics, University of Chittagong.
Author σ : Lecturer, Department of Statistics, University of Chittagong.
Author ρ : Assistant Professor, Department of Accounting and Information System, University of Chittagong, Bangladesh.
E-mail : mmrseu@yahoo.com

II. Literature Review

Contreras et al. (2003) used ARIMA models to predict next day electricity prices; they have found two ARIMA models to predict hourly prices in the electricity markets of Spain & California. The Spanish model needs 5 hours to predict future prices as opposed to the 2 hours needed by the Californian model. Kumar et al. (2004) used ARIMA model to forecast daily maximum surface ozone concentrations in Brunei Darussalam. They have found that ARIMA (1, 0, 1) was suitable for the surface O_3 data collected at the airport in Brunei Darussalam. Tsitsika et al. (2007) used ARIMA model to forecast pelagic fish production. The final model selected were of the form ARIMA (1, 0, 1) & ARIMA (0, 1, 1).

Azad et al. (2011) used ARIMA model in forecasting Exchange Rates of Bangladesh. By using Box Jenkins methodology they tried to find out best model for forecasting. They have found that ERNN (exchange rate neural network) model shows better performance than ARIMA. Merh (2011) used ANN & ARIMA models in next day stock market forecasting. They used ANN (4-4-1) and ARIMA (1, 1, and 1) for forecasting the future index value of sensex (BSE 30).

Global Journal of Management and Business Research (C) Volume XIII Issue III Version I Year 2013

The forecasting accuracy obtained for ARIMA (1,1,1) is better than ANN(4-4-1). Liv et al. (2011) used ARIMA model in forecasting incidence of hemorrhagic fever with renal syndrome in China. The goodness of fit test of the optimum ARIMA (0, 3, and 1) model showed non-significant autocorrelation in the residuals of the model.

Datta (2011) used ARIMA model in forecasting inflation in the Bangladesh Economy. He showed that ARIMA (1, 0, 1) model fits the inflation data of Bangladesh satisfactorily. Al-Zeaud (2011) used ARIMA model in modeling &forecasting volatility. The result shows that best ARIMA models at 95% confidence interval for banks sector is ARIMA (2, 0, and 2) model. Uko et al. (2012) examined the relative predictive power of ARIMA, VAR & ECM models in forecasting inflation in Nigeria. The result shows that ARIMA is a good predictor of inflation in Nigeria & serves as a benchmark model in inflation forecasting.

From the above mentioned studies it is clear that ARIMA can be used to forecast. In very few of them the authors tried to find out best ARIMA model, but in most of the articles the authors used ARIMA to forecast. The present study is designed to select the best ARIMA model to forecast average daily price index of listed companies in Dhaka Stock Exchange.

III. Objectives of the Study

Share price index is a time series data. One of the important objectives of the time series analysis is to study the past behavior of the available data and then forecast with fitting a suitable model with the help of econometric or statistical techniques. Thus, the specific objectives of this study are as follows:

1. To check whether the selected time series data is stationary or not. If not, the data are to be transformed into stationary using suitable transformation.
2. To select the best ARIMA model using some selection criteria. Then ARIMA techniques are applied to fit and forecast the average daily share price indices of DSE data for the Square Pharmaceuticals Limited (SPL) Company.
3. Finally, to draw a conclusion for forecasting the average daily share price indices of the selected company efficiently.

IV. Data and Methodology

The ADSPI data recorded against SPL have been collected from Dhaka Stock Exchange (DSE) for the year 2011. Thus we obtained a total of 236 observations against all working days from Square Pharmaceuticals limited.

The stepwise methodology used in this study is outlined below:

Firstly, the data is presented graphically to check whether the data series is stationary or not. For this purpose, the statistics like Ljung-Box-Pierce Q-statistic (1978) based on auto correlation; Dickey-Fuller test (DF) (1979), Augmented Dickey-Fuller (ADF) test (1982) based on unit root process have been applied.

To select the best ARIMA (p, d, q) type of models fitted for the company, their goodness of fit have been compared using following criteria;

a) The Akaike Information Criteria (AIC)
b) The Corrected Akaike Information Criteria (AICc)
c) Schwartz Information Criteria (SIC)
d) Mean Absolute Percent Error (MAPE)
e) Root Mean Square Error (RMSE) and
f) Absolute Mean Error (AME)

A brief description about the criteria for the selection of best ARIMA model is given below:

a) Akaike Information Criterion (AIC)

AIC is an important and leading statistics by which we can determine the order of an autoregressive model Mr. Akaike developed this statistics. According to his name this statistics is known as Akaike Information Criterion (AIC). The AIC takes into account both how well the model fits the observed series and the number of parameters to be used in the fit. AIC due to Akaike (1969) is defined as

$$\mathbf{AIC} = \mathbf{N}\left(\mathbf{In}\hat{\delta}^2 + 1\right) + 2(\mathbf{p} + 1)$$

Where the parameter bears the usual meaning. Akaike also mention that the minimum AIC criterion produced a selected model, which is hopefully closer to the best possible choice.

b) Corrected Akaike Information Criterion

Sometimes the AIC does not provide the efficient order of model selection, which asymptotic efficiency is more desirable criterion. Shibata in 1976 shown that AIC criterion is not consistent too. Thus Hurvich and Tsai (1989) provide a criterion of AIC for bias. The correlation is of particular use when the sample size is small or when the number of fitted parameter is a moderate to a large fraction of sample size. The criterion is defined as

$$\mathbf{AIC_c} = \mathbf{N}\ln\hat{\delta}^2 + \frac{1 + \frac{\mathbf{P}}{\mathbf{N}}}{1 - \frac{\mathbf{P}+2}{\mathbf{N}}}$$

i.e,

$$\mathbf{AIC_c} = \mathbf{AIC} + \frac{1 + \frac{\mathbf{P}}{\mathbf{N}}}{1 - \frac{\mathbf{P}+2}{\mathbf{N}}} = \frac{2(\mathbf{P}+1)(\mathbf{P}+2)}{(\mathbf{N}-\mathbf{P}+2)}$$

Thus AIC_c is the sum of AIC and an additional non-stochastic penalty term 2(p+1) (p+2) / (N-p+2), where the parameter bears the usual meaning.

c) Schwaetz Information Criteria

In 1978 Schwaetz discussed a criterion denoted by SIC which help in deciding the order of auto regression. Initially he developed this criterion for taking decisions about the regress subset. Later Engel et. al, in 1992 use this criterion as a tool for determining the order of auto regression and they defined this criterion as below

$$\mathbf{SIC} = \hat{\delta}\left(-\frac{\mathbf{p}}{\mathbf{N}}\right)^{\frac{1}{2}} \mathbf{N}^{\frac{\mathbf{p}}{2\mathbf{N}}}$$

Where, the parameters bear the usual meaning. Schwartz also shows that this criterion is better than AIC. The model with minimum SIC assumes to describe the data series adequately. The minimum value of this criterion is desirable for the adequacy of a model.

Criteria used for testing the validity of model

The criteria mentioned above are compared for correct determination of the order of auto regression and the degree of differencing and this criterion is computed only for estimation period. But for the selection of an ARIMA model, which adequately describes the data series, the values of the following criteria are compared for three periods viz, estimation period, validation period and total period. The criteria used in this study are as follows:

a) Absolute Mean Error (AME)
b) Root Mean Square Error (RMSE)
c) Mean Absolute Percent Error (MAPE)

d) Absolute Mean Error (AME)

The mean of the absolute deviation of predicted and observed values is called absolute mean error and is defined as

$$\mathbf{AME} = \sum_{\mathbf{I}=1}^{\mathbf{T}} \frac{\left|\mathbf{Z}_{\mathbf{obs}} - \mathbf{Z}_{\mathbf{pred}}\right|}{\mathbf{T}}$$

This criterion is used for the comparison of the models in three periods.

e) Root Mean Square Error (RMSE)

The square root of the sum of square of the deviation of the predicted values from the observed value dividing by their number of observation is known as the root mean square error. The root mean square error is defined as

$$\mathbf{RMSE} = \sqrt{\frac{1}{\mathbf{T}}\sum_{\mathbf{I}=1}^{\mathbf{T}}\left(\mathbf{Z}_{\mathbf{obs}} - \mathbf{Z}_{\mathbf{pred}}\right)^2}$$

Where, T is the number of periods. This criterion is used for the comparison of the models in three periods.

f) Mean Absolute Percent Error (MAPE)

The mean of the sum of absolute deviation of predicted and observed value dividing by the observed value is called mean absolute error. For comparison we have multiplied by 100, which is called mean absolute percent error and which is defined as

$$\mathbf{MAPE} = \frac{1}{\mathbf{T}}\sum_{\mathbf{t}=1}^{\mathbf{T}} \frac{\left|\mathbf{Z}_{\mathbf{obs}} - \mathbf{Z}_{\mathbf{pred}}\right|}{\mathbf{Z}_{\mathbf{obs}}} \times 100$$

Where, the parameters bear the usual meaning.

From the above discussion it is clear that the smaller error better the forecasting performance of the observed variables and if the model variable perform well, so will the model as a whole do too.

For the data series a separate ARIMA model has been used. For that purpose, a general concept of ARIMA (p, d, and q) model is discussed below:

ARIMA models are, in theory, the most general class of models for forecasting a time series that can be stationeries by transformations such as differencing and logging. If we have to difference a time series d times to make it stationary and then apply the ARMA (p, q) model to it, we can say that the original time series is ARIMA (p, d, q), that is it is an autoregressive integrated moving average time series, where p denotes the number of autoregressive terms, d denotes the time series have to be differenced before it becomes stationary and q denotes the number of moving average terms. Thus an ARIMA (2,1,2) time series has to be differenced once (d=1) before it becomes stationary and the stationary time series can be modeled as an ARMA (2,2) process that is it has two AR and two MA terms. Of course if d=0 then ARIMA (p, d=0,q) = ARMA (p, q). A most general ARIMA model constitutes three types of process named as autoregressive (AR) process, differencing to strip of the integration (I) and moving average (MA) process. The goodness of fit with respect to every criterion are examined and the model which satisfies most of the criterion, is considered as the best one.

Auto Regressive (AR) Process

In an autoregressive process each value in a series is linear function of the preceding value. Thus in the first order autoregressive process only the single preceding value is used as a function of current value. In the second order autoregressive process two preceding values are used as a function of the current value and so on. The first order autoregressive is denoted by AR (1), the second order autoregressive is denoted by AR (2) and up to the p^{th} order autoregressive is denoted by AR (p).

Let us suppose that the variable $\mathbf{Y_t}$ is a linear function of the preceding variable $\mathbf{Y_{t-1}}$. Therefore the model can be written as

$$\mathbf{Y_t} = \theta + \phi_1 \mathbf{Y_{t-1}} + \mathbf{u_t} \quad (1)$$

Where $\mathbf{u_t} \sim \mathbf{IN}\left(0, \sigma_u^{\ 2}\right)$

The model (1) is known as AR (1) model.
But if we consider the model

$$\mathbf{Y_t} = \theta + \phi_1 \mathbf{Y_{t-1}} + \varphi_2 \mathbf{Y_{t-2}} + \mathbf{u_t} \quad (2)$$

Where $\mathbf{u_t} \sim \mathbf{IN}\left(0, \sigma_u^{\ 2}\right)$

The model (2) is known as AR (2) model.
In general we can write

$$Y_t = \theta + \phi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots\ldots + \phi_p Y_{t-p} + u_t \quad (3)$$

Where ϕ_1 is known as the first order autoregressive coefficient, ϕ_2 is known as the second order autoregressive coefficient and so on
The model (3) is known as AR (p) model.

Differencing

Differencing is a comparatively simple operation that involves calculating consecutive changes in the values of the data series. Differencing is used when the mean of a series is changing over time to time. A consciousness that is homogeneously non-stationary can be transform into stationary by differencing. Differencing is not dealing with non-stationary variance. To difference a series once (d=1) we have to calculate the period to period change, to difference a series twice (d=2) we have to calculate the period to period changes in the first difference series and so on for further differences.

Moving Average

In Statistics, a moving average or rolling average is one of a family of similar techniques used to analyze time series data. It is applied in finance and especially in technical analysis. It can also be used as a generic smoothing operation, in which case the raw data need not be a time series.

A moving average series can be calculated for any time series. In finance it is most often applied to stock prices, returns or trading volumes. Moving averages are used to smooth out short-term fluctuations, thus highlighting longer-term trends or cycles. The threshold between short-term and long-term depends on the application, and the parameters of the moving average will be set accordingly.

Mathematically, each of these moving averages is an example of a convolution. These averages are also similar to the low-pass filters used in signal processing.

In moving average process, each value is determined by the average of the current disturbance and one or more previous disturbances. Suppose the model Y as follows:

$$\mathbf{Y_t} = \theta + \mathbf{u_t} + \beta_1 \mathbf{u_{t-1}} \quad (4)$$

Where θ is constant and u is the white noise error term i.e., u~N$\left(0, \sigma^2\right)$. Here Y at time t is equal to a constant plus a moving average of the current and past error terms. In this case, we say that Y follows a first order moving average or MA (1) process.
But if Y follows the expression

$$\mathbf{Y_t} = \theta + \mathbf{u_t} + \beta_1 \mathbf{u_{t-1}} + \beta_2 \mathbf{u_{t-2}} \quad (5)$$

Then we say that Y follows a second order moving average or MA (2) process.
In general,

$$\mathbf{Y_t} = \theta + \mathbf{u_t} + \beta_1 \mathbf{u_{t-1}} + \beta_2 \mathbf{u_{t-2}} + \ldots\ldots\ldots\ldots\ldots + \beta_q \mathbf{u_{t-q}} \quad (6)$$

Then we say that Y follows a q^{th} order moving average or MA (q) process.

In short, a moving average process is simply a linear combination of white noise error terms.

Characteristics of a good ARIMA model

Our main motivation is to build up a good ARIMA model in this study. The Characteristics of a good ARIMA model are as follows:

1. A good model is stationary, that is, it has an AR coefficient that satisfies some mathematical inequalities.
2. A good model is invertible, that is, it has MA coefficient, which satisfies some mathematical inequalities.
3. A good model is parsimonious i.e., uses the small number of coefficients needed to explain the available data.
4. A good model has statistically independent residuals.
5. A good model has high-equality estimated coefficient at the estimation stage.
6. A good model fits the available data sufficiently well at the estimation stage.
7. Root-Mean Squared Error (RMSE) is acceptable.
8. Mean-Absolute percent error (MAPE) is acceptable.
9. A good model has sufficiently small forecast errors i.e., it forecasts the future satisfactory.

Selection of ARIMA models for ADSPI of SPL data series

In order to identify the tentative ARIMA model for the ADSPI of SPL, the steps described by Box and Jenkins have been followed. For this purpose the data

Global Journal of Management and Business Research (C) Volume XIII Issue III Version I Year 2013

are partitioned into two stages. The first stage is known as the estimation stage and second is known as the validation stage. The sample of observations 1 to 226 has been used in estimation stage and the rest has been used for testing the validity of model.

Ten ARIMA models with tentatively selected various values of p, d and q are estimated by using computer software SHAZAM versions 8.0 for windows. The ten tentatively selected models are ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (2,1,1), ARIMA (2,1,2), ARIMA (1,1,3), ARIMA (2,1,3), ARIMA (3,1,1), ARIMA (3,1,2), ARIMA (3,1,3) and ARIMA (1,1,4). Among the models only five comparatively well performed models are displayed in the table -1c. Table- 1c discloses that ARIMA with p=2, d =1 and q=2 process has maximum number of lowest values of all the selected criteria AIC, AICc, SIC, and AME, RMSE, MAPE in the three periods i.e., estimation period, validation period and total period Hence, ARIMA (2,1,2) model has been selected for forecasting the ADSPI of SPL data series.

The fitted ARIMA (2, 1, and 2) model selected for SPL data series is given by

$$(1-0.6636^*B-0.60032^*B^2)\ SPL_{-t} = 0.0040125 + (1-0.44229^*B-0.489^*B^2)\ a_t$$

$$\quad(0.2925)\qquad(0.1737)\qquad\qquad\qquad\qquad(0.3036)\qquad(0.1971)$$

(Values in the parenthesis are corresponding t-values and '*' means statistical significance p<0.01)

V. Results and Discussion

The major findings of the study are as follows:

1. The upward trends of plots of the data series are visualized although the overall trends are not smooth.
2. The ACF and PACF plots of original data series show that the Average Daily Share Price Indices (ADSPI) of Square Pharmaceuticals Limited (SPL) are non-stationary, that is, most of the ACF and PACF plots are beyond the confidence limits shown in Figure- 1a.
3. From ACF and PACF plots of logarithmic transformation data series has been found that the ADSPI of SPL data series is still non-stationary, that is, all the ACF & PACF plots are out of the confidence limits.Shown in figure-1b. But after taking first difference of logarithmic values of SPL data series, the same plots shows that the data is stationary shown in Figure- 1c.
4. The Dickey-Fuller unit root test statistic and the Ljung-Box-pierce Q-Statistic also indicate that the Average Daily Share Price Indices (ADSPI) of SPL data series is non-stationary. The computed absolute values of the τ-statistic for SPL is found as $|\tau| = 1.7133$, none of which exceeds the DF or Mackinnon DF absolute critical τ values (to be noted that 1%, 5% and 10% level of significance the absolute DF values are 4.047, 3.462 & 3.13 respectively) shown in Table- 1a.
5. After taking first difference of logarithmic values of SPL data series, the same test statistic shows that the data is stationary, because hence the computed absolute value of the τ-statistic is $|\tau| = 4.2651$ which exceeds the DF or Mackinnon DF absolute critical τ values shown in Table- 1b.
6. For SPL data series ten types of tentatively ARIMA models with varied values of p, d & q are selected of which five-performed model for the data series are estimated and the validity of the model is tested by using AME, RMSE & MAPE for three different period shown in Tabil -1c.
7. It is found that ARIMA (2, 1, 2) is the best model for forecasting the SPL data series.
8. Finally, the Average Daily Share Price Indices (ADSPI) for Square Pharmaceuticals Limited (SPL) data series have been forecasted by using the selected model and reported in table- 1d.

Table 1(a) : The values of the various stationary tests of the company for average daily share price indices of DSE data series

Test Statistic		SPL
Ljung-Box-Pierce Q-statistic	Time lag-10	1947.02
	Time lag-20	2999.72
Dickey-Fuller test		-1.7133

At 1%, 5% and 10% level of significance the DF values are –4.047, -3.462 and –3.13 respectively.

Table 1(b) : Values of Dickey-Fuller test statistic for different values of differencing of Logarithmic Transformation SPL data series

Difference	SPL
0	-1.6605
1	-4.2651
2	-10.027

VI. Conclusion

This study made the best endeavor to develop the best ARIMA model to efficiently forecasting the Average Daily Share Price Indices (ADSPI) of the Square Pharmaceuticals Limited (SPL), because if it is possible to provide a better model for the share market which can enable the investors to predict the prices in advance, it would help the investors as well as stability of the national economy. The empirical analysis indicated that the ARIMA (2,1,2) model is best for forecasting the Average Daily Share Price Indices (ADSPI) of the Square Pharmaceuticals Limited (SPL) data series so far the diagnostic criteria are concerned. Finally, the Average Daily Share Price Indies (ADSPI) for Square Pharmaceuticals Limited (SPL) data series is forecasted up to February, 2012 by using the selected model.

References Références Referencias

1. Al-Zeaud, H.A. (2011) "Modeling &Forecasting Volatility using ARIMA model", *European Journal of Economics,* Finance & Administrative Science, Issue 35, pp. 109-125.
2. Azad, A.K. & Mahsin, M. (2011) "Forecasting Exchange Rates of Bangladesh using ANN & ARIMA models: A comparative study, *International Journal of Advanced Engineering Science & Technologies*, Vol. No. 10, Issue No. 1, pp. 031-036.
3. Contreras, J., Espinola, R., Nogales, F.J. and Conejo, A.J. (2003) "ARIMA models to predict Next Day Electricity Prices," *IFEE Transactions on power system*, Vol. 18, No. 3, pp 1014-1020.
4. Datta, K. (2011) "ARIMA Forecasting of Inflation in the Bangladesh Economy", *The IUP Journal of Bank Management*, Vol. X, No. 4, pp. 7-15.
5. Kumar, K.; Yadav, A.K.; Singh, M.P.; Hassan, H. and Jain, V.K. (2004) "Forecasting Daily Maximum Surface Ozone."
6. Concentrations in Brunei Darussalam- An ARIMA Modeling Approach", *Journal of Air & Waste Management and Association*, Volume 54, pp 809-814.
7. Liv, Q.; Liu, X.; Jiang, B. & Yang, W. (2011) "Forecasting incidence of hemorrhagic fever with renal syndrome in China using ARIMA model", *Biomed Central*, pp. 1-7.
8. Merh, N.; Saxena, V.P. & Pardasani, K.R. (2011) "Next Day Stock market Forecasting: An Application of ANN & ARIMA", *The IUP Journal of Applied Science*, Vol. 17 No. 1, pp. 70-84.
9. Tsitsika, E.V.; Maravelias, C.D & Haralatous, J. (2007) "Modeling & forecasting pelagic fish production using univariate and multivariate ARIMA models", *Fisheries Science*, Volume 73 pp 979-988.
10. Uko, A.K; Nkoro, E. (2012) "Inflation Forecasts with ARIMA, Vector Autoregressive & Error Correction Models in Nigeria", *European Journal of Economics, Finance & Administrative Science*, Issue 50, pp. 71-87.

Appendix

Figure 1 (a) : The ACF and PACF plots of original data for average daily share price indices of SPL data series

```
                                                 0      0 0
AUTOCORRELATION FUNCTION OF THE SERIES         (1-B) (1-B) AVG

 1 0.98 .                             +   RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR.
 2 0.96 .                         +       RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR.
 3 0.95 .                       +         RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR .
 4 0.93 .                      +          RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR .
 5 0.91 .                    +            RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR  .
 6 0.89 .                   +             RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR   .
 7 0.87 .                  +              RRRRRRRRRRRRRRRRRRRRRRRRRRRRRR    .
 8 0.84 .                 +               RRRRRRRRRRRRRRRRRRRRRRRRRRRRRR    .
 9 0.81 .                +                RRRRRRRRRRRRRRRRRRRRRRRRRRRRR     .
10 0.78 .               +                 RRRRRRRRRRRRRRRRRRRRRRRRRRRR      .
11 0.75 .               +                 RRRRRRRRRRRRRRRRRRRRRRRRRRR       .
12 0.73 .              +                  RRRRRRRRRRRRRRRRRRRRRRRRRR        .
13 0.70 .              +                  RRRRRRRRRRRRRRRRRRRRRRRRR         .
14 0.67 .             +                   RRRRRRRRRRRRRRRRRRRRRRRR          .
15 0.65 .             +                   RRRRRRRRRRRRRRRRRRRRRRR           .
16 0.62 .            +                    RRRRRRRRRRRRRRRRRRRRRR            .
17 0.60 .            +                    RRRRRRRRRRRRRRRRRRRRR+            .
18 0.58 .            +                    RRRRRRRRRRRRRRRRRRRRR+            .
19 0.56 .           +                     RRRRRRRRRRRRRRRRRRRR  +           .
20 0.54 .           +                     RRRRRRRRRRRRRRRRRRR   +           .
21 0.52 .           +                     RRRRRRRRRRRRRRRRRRR   +           .
22 0.50 .          +                      RRRRRRRRRRRRRRRRRR     +          .
23 0.49 .          +                      RRRRRRRRRRRRRRRRRR     +          .
24 0.48 .          +                      RRRRRRRRRRRRRRRRR      +          .
```

```
                                                    0      0 0

PARTIAL AUTOCORRELATION FUNCTION OF THE SERIES   (1-B)(1-B) AVG

 1 0.98 .                             +   RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR.
 2 0.13 .                             +   RRRRRR                            .
 3 0.02 .                             +   RR  +                             .
 4 -.13 .                             RRRRR   +                             .
 5 -.02 .                             +  RR   +                             .
 6 -.06 .                             + RRR   +                             .
 7 -.12 .                             RRRRR   +                             .
 8 -.13 .                             RRRRR   +                             .
 9 -.01 .                             +   R   +                             .
10 -.10 .                             RRRRR   +                             .
11 0.08 .                             +   RRRR+                             .
12 0.09 .                             +   RRRR+                             .
```

Figure 1 (b) : The ACF and PACF plots of Logarithmic Transformation data for average daily share price indices of SPL data series

```
                                                         0      0 0
 AUTOCORRELATION FUNCTION OF THE SERIES                (1-B) (1-B)   X

 1 0.98 .                             +   RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR.
 2 0.97 .                         +       RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR.
 3 0.96 .                       +         RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR .
 4 0.94 .                      +          RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR .
 5 0.92 .                    +            RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR  .
 6 0.91 .                   +             RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR  .
 7 0.89 .                  +              RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR   .
 8 0.86 .                 +               RRRRRRRRRRRRRRRRRRRRRRRRRRRRRR    .
 9 0.84 .                +                RRRRRRRRRRRRRRRRRRRRRRRRRRRRRR    .
10 0.82 .               +                 RRRRRRRRRRRRRRRRRRRRRRRRRRRRR     .
11 0.80 .              +                  RRRRRRRRRRRRRRRRRRRRRRRRRRRR      .
12 0.78 .              +                  RRRRRRRRRRRRRRRRRRRRRRRRRRR       .
13 0.76 .             +                   RRRRRRRRRRRRRRRRRRRRRRRRRRR       .
14 0.74 .             +                   RRRRRRRRRRRRRRRRRRRRRRRRRR        .
15 0.71 .            +                    RRRRRRRRRRRRRRRRRRRRRRRRR         .
16 0.70 .            +                    RRRRRRRRRRRRRRRRRRRRRRRRR         .
17 0.68 .           +                     RRRRRRRRRRRRRRRRRRRRRRRR          .
18 0.66 .           +                     RRRRRRRRRRRRRRRRRRRRRRR           .
19 0.64 .          +                      RRRRRRRRRRRRRRRRRRRRRRR+          .
20 0.62 .          +                      RRRRRRRRRRRRRRRRRRRRRR +          .
21 0.61 .          +                      RRRRRRRRRRRRRRRRRRRRRR +          .
22 0.59 .         +                       RRRRRRRRRRRRRRRRRRRRR   +         .
23 0.57 .         +                       RRRRRRRRRRRRRRRRRRRRR   +         .
24 0.56 .         +                       RRRRRRRRRRRRRRRRRRRR    +         .
```

```
                                                             0      0 0
PARTIAL AUTOCORRELATION FUNCTION OF THE SERIES             (1-B) (1-B)   X

 1 0.98 .                             +   RRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRRR.
 2 0.15 .                             +   RRRRRR                            .
 3 0.03 .                             +   RR  +                             .
 4 -.11 .                             RRRRR   +                             .
 5 -.01 .                             +   R   +                             .
 6 -.05 .                             + RRR   +                             .
 7 -.09 .                             +RRRR   +                             .
 8 -.09 .                             +RRRR   +                             .
 9 0.01 .                             +   R   +                             .
10 -.11 .                             RRRRR   +                             .
11 0.04 .                             +   RR  +                             .
12 0.08 .                             +   RRRR+                             .
```

Global Journal of Management and Business Research (C) Volume XIII Issue III Version I Year 2013

Figure 1 (c) : The ACF and PACF plots of Logarithmic Transformation data for average daily share price indices of SPL data series with difference one

```
                                                    1      0 0
 AUTOCORRELATION FUNCTION OF THE SERIES           (1-B) (1-B)  X

  1 -.23 .                        RRRRRRRRR   +                       .
  2 0.00 .                           +    R    +                      .
  3 0.13 .                           +    RRRRR+                      .
  4 -.03 .                           +   RR    +                      .
  5 0.06 .                           +    RRR  +                      .
  6 0.09 .                           +    RRRR +                      .
  7 0.09 .                           +    RRRR +                      .
  8 -.05 .                           +  RRR    +                      .
  9 0.14 .                           +  RRRRRR +                      .
 10 -.08 .                           + RRRR    +                      .
 11 -.03 .                           +   RR    +                      .
 12 0.04 .                           +    RR   +                      .
 13 0.06 .                           +    RRR  +                      .
 14 -.03 .                           +   RR    +                      .
 15 -.11 .                           +RRRRR    +                      .
 16 0.11 .                           +    RRRRR+                      .
 17 -.10 .                           + RRRR    +                      .
 18 -.03 .                           +   RR    +                      .
 19 -.02 .                           +   RR    +                      .
 20 -.04 .                           +   RR    +                      .
 21 0.10 .                           +    RRRR +                      .
 22 -.19 .                         RRRRRRR     +                      .
 23 -.05 .                           +  RRR    +                      .
 24 0.09 .                           +    RRRR +                      .

                                                           1      0 0
PARTIAL AUTOCORRELATION FUNCTION OF THE SERIES           (1-B) (1-B)  X
  1 -.23 .                        RRRRRRRRR   +                       .
  2 -.05 .                            + RRR   +                       .
  3 0.12 .                            + RRRRR +                       .
  4 0.03 .                            +   RR  +                       .
  5 0.07 .                            +   RRRR+                       .
  6 0.11 .                            +   RRRRR                       .
  7 0.15 .                            + RRRRRR+                       .
  8 -.01 .                            +   R   +                       .
  9 0.12 .                            +   RRRRR                       .
 10 -.06 .                            + RRR   +                       .
 11 -.08 .                            +RRRR   +                       .
 12 -.06 .                            + RRR   +                       .
```

Table 1 (c) : The values of diagnostic criteria for ARIMA model for logarithmic transformation difference series of average daily share price indices of DSE data of Square Pharmaceuticals limited

Transformation Difference=1

Criteria	Period	Validation of diagnostic criteria for the model				
		ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (1,1,3)	ARIMA (2,1,1)	ARIMA (2,1,2)
AIC	Estimation	-6.4781	-6.5012*	-6.4729	-6.4797	-6.4679
AICc	Estimation	-6.4275	-6.4506*	-6.4223	-6.3780	-6.3662
SIC	Estimation	-6.4339	-6.4423*	-6.3993	-6.4208	-6.3943
AME	Estimation	0.00098364	0.0010903	0.00096091	0.00093692	0.0008849*
	Validation	0.00096132*	0.0011192	0.0010414	0.0014722	0.0024209
	Total	0.00060532	0.0006709	0.00059133	0.00057657	0.0005446*

RMSE	Estimation	0.0039346	0.0043614	0.0032933*	0.0037477	0.0035398
	Validation	0.0030400*	0.0035393	0.0038436	0.0046554	0.0076556
	Total	0.0030865	0.0034213	0.0030152	0.0029399	0.0027768*
MAPE	Estimation	0.000028956	0.00003209	0.000028287	0.00002758	0.0000260*
	Validation	0.00002981*	0.00003470	0.000032293	0.00004565	0.0000751
	Total	0.000017819	0.00001995	0.000017407	0.00001697	0.0000160*
No. Of lowest values		03	03	01	0	05

Note: A '*' (starlet) indicate the lowest value in each row.

Table 1 (d) : The observed and forecasted values with its lowest and highest values obtained by ARIMA (2,1,2) model for ADSPI of SPL data series

Future Date	Lower	Forecast	Upper	Actual	Error
220	8.04513	8.11908	8.19303	8.11731	-0.176589E-02
221	8.03266	8.12080	8.20894	8.08148	-0.393235E-01
222	8.02160	8.12278	8.22396	8.06621	-0.565736E-01
223	8.01207	8.12475	8.23742	8.08148	-0.432712E-01
224	8.00361	8.12671	8.24981	8.09132	-0.353913E-01
225	7.99597	8.12868	8.26139	8.07683	-0.518527E-01
226	7.98898	8.13064	8.27231	8.16990	0.392577E-01
227	7.98252	8.13261	8.28271	8.07869	-0.539229E-01
228	7.97650	8.13458	8.29265	8.08487	-0.497067E-01
229	7.97088	8.13654	8.30221	8.08364	-0.529064E-01
230	7.96558	8.13851	8.31144	8.09040	-0.481075E-01
231	7.96058	8.14048	8.32037	8.07652	-0.639606E-01
232	7.95584	8.14244	8.32904	8.07714	-0.653055E-01
233	7.95133	8.14441	8.33749	8.15306	0.865358E-02
234	7.94703	8.14637	8.34572	8.08425	-0.621205E-01
235	7.94292	8.14834	8.35376	8.19395	0.456122E-01
236	7.93899	8.15031	8.36162	8.12356	-0.267491E-01
237	7.93522	8.15227	8.36933		
238	7.93159	8.15424	8.37688		
239	7.92811	8.15621	8.38430		
240	7.92475	8.15817	8.39160		
241	7.92150	8.16014	8.39877		
242	7.91837	8.16210	8.40583		
243	7.91535	8.16407	8.41279		
244	7.91242	8.16604	8.41965		
245	7.90959	8.16800	8.42642		
246	7.90684	8.16997	8.43310		
247	7.90417	8.17194	8.43970		
248	7.90159	8.17390	8.44622		
249	7.89908	8.17587	8.45266		
250	7.89664	8.17783	8.45903		
251	7.89427	8.17980	8.46533		
252	7.89196	8.18177	8.47157		
253	7.88971	8.18373	8.47775		
254	7.88753	8.18570	8.48387		
255	7.88540	8.18766	8.48993		
256	7.88333	8.18963	8.49593		
257	7.88131	8.19160	8.50189		
258	7.87934	8.19356	8.50779		
259	7.87741	8.19553	8.51364		
260	7.87554	8.19750	8.51945		
261	7.87371	8.19946	8.52521		
262	7.87193	8.20143	8.53093		
263	7.87018	8.20339	8.53661		
264	7.86848	8.20536	8.54224		
265	7.86682	8.20733	8.54784		
266	7.86519	8.20929	8.55339		

267	7.86360	8.21126	8.55891		
268	7.86205	8.21323	8.56440		
269	7.86054	8.21519	8.56985		

This page is intentionally left blank